Artificial Intelligence: Adaptation Into Current Biomedical Engineering and Its Coefficient of Difficulty?

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Abstract

Artificial Intelligence (AI) is a gigantic, developing subject used comprehensively in the continuous period of Biomedical Engineering, where scientists are investigating all the purposes of artificial intelligence and contemplating how to foster it. The accuracy of AI is enhanced through daily improvement, and the current prediction using AI is evaluated by its accuracy in this literature review. The present achievement of AI in healthcare is discussed with future applications. As AI is an arising innovation, its downsides are inevitable and considered. This review summarizes the unsolved questions and difficulties clinics and engineers face individually.

Keywords: ***artificial intelligence, biomedical engineering***

1. Introduction

Artificial intelligence is a recently developing and ongoing field in the biomedical engineering; however, it has long term history can be traced back to the third century. The first humanoid automaton is mentioned in China in the third century, when a mechanical engineer named Yan Shi presented the Emperor Mu of Zhou a humanoid automaton made of leather, wood, and fake organs. The next significant moment is when Leonardo da Vinci designed his humanoid robot after conducting in-depth research on human anatomy during the Renaissance [1]. Only in the 1950s were his 1495 sketches rediscovered. The knight robot used by Leonardo da Vinci could move its head and jaw, stand up, and sit down. It could also wave its arms. Even though these movements were controlled by cables and pulleys behind it and unable to assist in practice, the concept from da Vinci has inspired a group of scientists' research in the robotic surgery field and named the project by his name for commemorate.

The existence of AI can be revolutionized and essential to the clinics by resolving time-consuming tasks and complexity analysis of data such as exploration of the protein structures using AlphaFold [2]. By displaying images of the patient's internal organs and assessing their condition, medical-image diagnostic systems are vital in disease diagnosis and prediction [3]. Future applications of AI are discussed alongside current achievements in healthcare. Robotic surgery can be made more humane and applicable to more different procedures than just auxiliary procedures. Since AI is a new technology, its drawbacks are inevitable and are being considered. In addition, this paper had outlined the difficulties and obstacles that engineers and clinics encountered when utilizing AI.

2. AI Accuracy in Prediction

When used for analysis, diagnosis, and prediction, artificial intelligence has an elevated degree of accuracy. These capacities are improved because of their program being modified. This paper explicitly features the development of artificial intelligence in the field of biomedical engineering over the past few years.

2.1 *AlphaFold*

The Critical Assessment of protein Structure Prediction (CASP) experiments congregate groups of engineers internationally [2]. By incorporating more physical and biological information about protein structure into the deep learning algorithm, a superior version of AlphaFold 2 was published in the most recent CASP14. Its accuracy increased from producing 24 out of 43 free modelling domains (Andrew W. Senior, 2020) published in CASP13 to 87 out of 92 domains in CASP14 (John Jumper, 2021). By looking at the data alone, it shows an extraordinary progress in how AI are assisting scientists in the biomedical field. In particular, AlphaFold can foresee underspecified protein structures such as intertwined homomers or proteins only fold in the presence of an unknown haem group, this greatly benefited the entire clinical methodology and expand on the ongoing proficiencies about proteins. In that future, researchers could investigate taking care of perplexing issues happening in the nature and enhance the utilization of clinical meds to make them more designated from being disturb by the unfamiliar proteins.

2.2 *Rayvolve®*

According to Dupuis et al. l (2022), a team of researchers used digital radiographs from a real-life cohort of children who regularly returned to the emergency room to compute the diagnostic performance of a deep learning algorithm [4]. Results showed high sensitivity and negative predictive value persisting in all the subgroup analyses except children with casts between the age of 4-18, for younger patients in the 0-4-year-old group the data was only acceptable but not accurate, the reason may be the young infants are having more cartilaginous structures, which can be hard to distinguish the difference with the matured bone structures. Even though in general the deep learning algorithm contribute a remarkable accuracy of 92.6%, sensitivity of 95.7% and specificity of 91.2% regarding detection approach, it's still not advanced. Most of the fractures that were missed by the algorithm were located on the tiny crevices such as phalanges and elbows, and the algorithm diagnose fractures only, it cannot differentiate between fractures and other bone-related oddities, for instant, it was not trained to detect dislocation, non-traumatic disorders, and soft tissue abnormalities. With persistent algorithm improvements this method can be adapt into clinical radiology and assists radiologists as a method of achieving optimal performance in diagnose, so that largely save the time efforts and reduced inaccuracy.

Despite the fact that we set great expectations on AlphaFold and deep learning algorithm, we ought to obviously advise ourselves that their mechanisms are tools to assist us with tackling issues that are holding us back, that they are not prepared to shape ground-breaking thoughts, and that as scientists we should not over-rely on these algorithms.

3. Pros of Using Artificial Intelligence in Biomedical Engineering

3.1 *Benefits and success of AI application*

In studies, AI were intended to give real-time data which helps in optimize critical clinical decisions, generate rapid results and improve accuracy of manual interpretation of the results. As the Rayvolve® mentioned above, the goal to achieve is the assist the radiologists in diagnose fractures, particularly in tough spots during youth. This study demonstrates that the pediatric appendicular skeleton algorithm performs well in diagnosis, particularly, it has high sensitivity and negative predictive value, proving the reliability of this AI algorithm in detecting children's fractures in the age of 5-18 years old without cast. At the point when clinics consolidate machine learning and deep learning algorithms, the efficiency and effectiveness of analysis using artificial intelligence would be to a great extent gotten to the next level.

With the rapid advancement of hardware and software applications, a significant part of the work at first performed by humans is being transferred to artificial intelligence that is more accurate and time effective than humans. Also, these techniques allow a share of data through the internet to provide information for clinical research and disease diagnose by doctors. For example, the Cancer Genome Atlas Program which has molecularly characterised over 20,000 primary cancers, containing 2.5 petabytes data and the UK Biobank which contains health information from nearly half of the UK citizens [1]. Most of these databases are public online, containing in-depth genetic information for researchers to undertake vital research, we can search the name of the database directly and the webpage will come out. [https://www.ukbiobank.ac.uk] Both constructed a solid bases of information for conducting clinical research and diagnosing diseases or cancers by contributing enormously amount of real-life data from patients and the country, saving human resources for disposal data.

One practical success of using AI in healthcare is the automated medical-image diagnosis, where many medical specialities rely on. The most widely used and well-known one is the radiology which used to detect and diagnose diseases, to identify the cause of illness and to monitor the patient trajectory during the course of a disease. Most of its application in X-ray radiography, computed tomography, magnetic resonance imaging and positron-emission tomography are the basic examines in the hospital [5]. In the image-based diagnosis, a technique known as transfer learning attempt to make neural network models more interpretable. Researchers collect millions of natural and non-medical images with finetune neural network connections using thousands of biomedical images. This is used to reduce the size of training samples require to train a neural network and improving the accuracy of classifying images. To visualize the neural network models, each pixel that is relevant are investigated. The diagnosis of pulmonary tuberculosis and lung diseases with chest radiography have reached expert-level diagnostic accuracies with this application [6]. In dermatology, diagnosing skin lesion and benign using automated diagnostic systems is working to apply in the healthcare. Due to from a picture AI cannot accurately detect the enlargement of the surface of the lesion or evolving lesion, it could not be used to replace the ABCDE rule that requires doctor.

3.2 *Futuristic adaptations*

Artificial Intelligence has changed the healthcare practices. From the patients' viewpoint, innovations like appointment-scheduling, deciphering clinical details and tracking histories have become readily available. From the specialists' aspect, transcribing notes, diagnosis, follow-up clinical cares and endorse individual medication plans have all brought comfort [7,8].

Not all the techniques are developed and able to well-adapt into clinical system at this stage, for example the diagnose of malignant lesions. We hope in the near future, accuracy could improve, and lower down the cost of training the deep-learning model, thus moving the diagnose from hospital to mobile devices, potentially improving the accessibility of skin-lesion screening at the expert level globally.

Wearable devices can assist and monitor movement, heart rate, blood pressure and blood sugar level of patients. Some examples of detection are early inflammatory responses; cardiovascular diseases by photoplethysmography sensors; Parkinson's disease with tremor [9]. Other than detective wearable devices, implantable wearing devices plays another important role in clinics. One major device is the cardiac pacemaker, adjusting the patient's heart rate which is necessity to their life. Scientists currently fostered bioresorbable cardiac pacemaker and conduct experiments in vivo on rats. This tackled current problems, for example, the removal of a pacemaker and this technique can be adapted to other energy-required components. Furthermore, with the application of AI into those wearable devices such as real-time monitor and immediate report can enhance the ability of those devices thus increase the prime time for treatment.

The da Vinci surgical system allows surgeons operate the robot from a console which is approved by the FDA, is a practical use of robotic surgery in clinics, enhancing the accuracy of operate [9,10]. Practical use of AI in clinic allows physicians to concentrate on more sophisticated task and enabling them to spend more time in operating room or discussing treatment plans with patients, therefore, its only robotically assisted surgery, not an autonomous robotic surgery. An autonomous robotic surgery, is where systems expedite the procedures of surgery, smothering the precise motions and increasing accuracy. This requires the AI to have decision-making, facilitate disease diagnosis and identify unrecognized imaging. Yet, it's in the developing stage, in the foreseeable future, AI surgery will be revolutionized and enhance the surgery process.

4. Limitations of application of Artificial Intelligence in Biomedical Engineering

On the other hand, to apply a successful well-trained deep learning algorithm into any field such as the healthcare systems would be facing many challenges and limitations. In this section, we will be discussing the facts and focusing more on the application in Biomedical Engineering region.

4.1 *Selection and obtainable of data*

To create an artificially intelligent system requiring vast amount of high-qualified data that had been selected cautiously by the scientists to ensure the data is specified in the region of adaptation, ensuring the output is valid [11]. Moreover, high supervision is required during the interpretation of results. Take AlphaFold for instance, which is a well-trained Artificial Intelligence system that able to process biological and physical information such as unfold the 3-D protein structure [2]. To ensure the accuracy of the analysis by AlphaFold, a group of scientists from the DeepMind company was designing the algorithm over years and input millions of protein samples in, lastly bringing about a generally positive result of 87 out of 92 domains, not precisely exact.

4.2 *Data collection and privacy*

The accessibility of large quantities of high-quality data could be low, which prompts an issue of data collection. The privacy of patient will in general be difficult to guarantee, as in late occurrences, major corporations are disclosing personal data, which brings about an adverse impact among patients and a restriction of accessing information. This could lead to limited model training, and consequently a fully conducted potential of a model might not be explored.

4.3 *Biased data and outcome*

The models could be shaped in predisposition. As the training data set collected is biased, for instant, only collect data from a particular race, the final model will not be able to conclude and anticipate the whole human race. This diminishes the utilize of model. As the creation of a model requires many procedures, the overall time consumed would be large. Any input of uncleared or biased data will affect the overall outcome of the model and shape the system differently from intended objective, therefore dissipate the time endeavors that were placing in to the design, adjust and process of the model.

5. Difficulties faced by engineers in using artificial intelligence

5.1 *Insufficient artificial intelligence skills*

Professionals with experience in AI and data science are hard to find. Data engineers, business intelligence analysts, software engineers, ML engineers, and SMEs must work in an interdisciplinary team for AI projects. This requirement is most evident in the manufacturing industry, where many young data scientist engineers are uninterested, repetitious, and tedious [12]. This problem is further exacerbated by a severe labor shortage in manufacturing expected to occur within the next decade when the baby boomers retire. Key technologies like AI automation and AutoML 2.0 may close the skills gap and hasten the digital industrial revolution.

5.2 *Leveraging data and inability to access*

Extremely difficult working conditions are typical of factory floors and heavy industrial environments. Fluctuating environmental variables such as temperature, pressure, dust, and vibration can lead to noisy and inaccurate data. According to Simulation/IT (2021), production facilities are likely to be far away, which will make data storage even more difficult [13]. Due to security concerns, IT engineers may also decide not to send data to the cloud and must address it on-premises.

5.3 *Real-time response requirements*

In the so-called "Industry 4.0", condition monitoring processes are a typical case where real-time application data from equipment is being examined using streamlined analytics to ensure optimal operation. Numerous industrial applications, such as predictive quality as well as maintenance, are sensitive to delays and require an incredibly fast response. For these applications, the system must analyze the data immediately to gain insights that may be used. The choice should be real-time, executed in milliseconds. Edge computing can help in such situations. To react quickly, it makes local data processing more efficient, close to the source [12]. Edge-based computing is required for local control systems and real-time decision-making. Smart manufacturing applications must be able to install hardware for predictive models at the edge, such as local gateways, machines, or servers.

5.4 *Interoperability of infrastructure and technology*

Plant engineers are responsible for choosing which converters, sensors or places and how best to connect their devices and systems without a common and standard framework. Engineers often work with a variety of tools, equipment, and production systems that use a variety of different and sometimes conflicting engineers. Some of these devices may even use outdated software that does not match other systems.

5.5 *Edge Deployment*

There are various applications for edge computing in manufacturing that may help engineers process data locally, sort and filter it, and send less of it to a master server, whether in the cloud or in the field. Smart manufacturing applications must be able to install predictive models on edge hardware, such as local gateways or servers and machines. The ability to leverage data from several devices, systems, and processes in order to modify manufacturing processes in real time is another important goal for contemporary manufacturing. To determine the best course of action based on data insights, this precise monitoring and control of industrial assets and processes employs large amounts of data, machine learning, and edge-based computing [13].

6. Difficulties faced by biologists/ doctors/clinics in using AI

6.1 *Insufficient medical data*

Clinicians, physicians and medical professionals need high-quality datasets to perform scientific and technical validation of AI models. However, collecting patient data and images to test algorithms is difficult due to the diversity of medical data available on numerous EHRs and software platforms. The incompatibility of medical data from one institution with other platforms is a significant barrier to AI in healthcare due to interoperability issues. According to the 2018 HIMSS Media Survey, only 38% of systems can automatically distinguish between language, medical symbols and code values. The healthcare industry must focus on standardized medical data to expand the amount of data available for testing AI systems.

6.2 *Bias and inequality in algorithms*

If biased data is used to train AI-driven applications, algorithms may provide inaccurate conclusions. The information used in training models is collected from non-stationary environments, such as clinics that serve various populations and have dynamic operational processes. When creating algorithms using data collected in dynamic environments, demographic trends and adjustments in clinical practice may introduce bias. Patient socioeconomic, gender, and ethnic characteristics may also be biased. For example, patients in rural areas may receive less accurate estimates from AI-generated data from research universities in large cities. Worse, the model may exacerbate disparities that already exist in the healthcare system rather than correctly reflecting objective reality.

6.3 *Deficiencies in research methodology*

According to Jiang et al. l, (2012), there are not enough established methodologies, prospective trials, or peer-reviewed studies of artificial intelligence in healthcare [14]. Many of the studies were retrospective, meaning that they used only medical records of patients who had already been diagnosed in the past. However, in order for physicians to fully understand the true value of AI diagnostic and treatment software in the real world, long-term studies (prospective studies) must be conducted on current patients. The validity of AI studies is compromised by the lack of peer-reviewed and randomized controlled trials (RCTs). According to research published in The Lancet in 2019, an AI platform that performs well in certain prospective trials does not perform as accurately in RCTs as senior physicians.

6.4 Transparency and interpretability

Understanding how AI can make diagnoses or predictions for the healthcare industry is critical, especially for clinical decision support systems (CDSSs). This requires an understanding of the underlying inputs and features used to make specific predictions. Black-box models are used for traditional AI solutions such as artificial neural networks (ANNs). This means that you cannot know the inference process of the system. One of the main difficulties and drawbacks of deploying AI in its current form in healthcare is transparency and interpretability [15]. In a 2020 paper entitled "Three Ghosts of Healthcare AI," experts concluded that iterative knowledge discovery approaches are limited by the inability to understand how the system generates recommendations.

6.5 Missing variables and confounding factors

Machine learning algorithms driven by AI use all available input data to improve performance. When AI systems take into account variables that researchers did not anticipate, results may be affected [16]. For example, some algorithms flag skin lesions on dermoscopic images as malignant because they include skin marks or scales from surgery. Based on x-ray scans from Mount Sinai Hospital, another AI system successfully identified individuals at high risk for pneumonia. However, it still performed much worse when using photos from other hospitals. One problem that proved unpredictable to the researchers was that the system may have identified high-risk patients at the original hospital by identifying which devices scanned critically ill patients.

7. Conclusion

To summarize all the points above, Artificial Intelligence has a promising future and could revolutionize the field of biomedical engineering. On the positive side, the difficulties that have been unearthed are keys to future development. In recent years, the accuracy of AI has gradually improved, which helps to improve clinical applications. In the near future, it is hoped that AI will lead to more comprehensive breakthroughs and innovations.

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